Consequences of Choosing Different Settings When Processing Hip-Based Accelerometry Data From Older Adults: A Practical Approach Using Baseline Data From the SITLESS Study

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Abstract

Accurately measuring older adults' physical activity (PA) and sedentary behavior (SB) using accelerometers is essential, as both are important markers of health. This study aimed to highlight how steps taken during data processing may affect key hip-based accelerometry outcomes in older adults, using a selection of baseline accelerometry data (n=658) from the xxxxx study. Different analytical parameters tested included wear-time algorithms, use of low-frequency extension (LFE) filter, epoch length, minimum and maximum daily wear-time thresholds. These were compared against vertical axis counts per minute (CPM), vector magnitude (VM) CPM, SB, light PA, moderate-vigorous PA, step counts and wear-time percentage. Differences in settings across the analytical parameters were assessed using paired sample t-tests and repeated measures ANOVAs using Bonferroni correction. Using the 'Choi 2011' versus 'Troiano 2007' wear-time algorithm resulted in a higher percentage wear-time. Most SB and PA outcomes were significantly different across wear-time algorithms ($p<0.001$). This was similar when using the LFE filter versus normal filter ($p<0.001$). Using 10-second epoch length increased daily SB time (between +75.7 and +79.2 minutes) compared to 60-second. Most SB and PA outcomes significantly changed comparing minimum-wear-time thresholds of 360, 480, 600 and 720 minutes per day ($p<0.001$). Applying a log-diary with a ≥1140-minute threshold had a significant impact on vertical axis CPM, VM CPM, SB and light PA outcomes ($p<0.001$). This study demonstrates the potential variability in the number of participants being included in studies and reported SB and PA levels when processing older adults' accelerometry data dependent on the analytical procedures utilized.

Keywords: accelerometer, ActiGraph, measurement, methodology, physical activity, sedentary behaviour

Introduction

Ageing has been associated with reductions in physical activity levels (PA) and increases in sedentary behavior (SB) (van Schooten et al., 2018). Lack of PA and excessive SB are considered key modifiable lifestyle risk factors associated with the progression of chronic diseases such as diabetes, cardiovascular disease, stroke and certain cancers as well as all-cause mortality risk (Bangsbo et al., 2019; Chau et al. 2013, Ding et al., 2016; Dogra et al., 2012; Ekelund et al., 2016; Lee et al., 2012; Rezende et al., 2014).

Accurately measuring PA and SB in older adults is important to more correctly understand how active and sedentary populations might be, to measure the associations between PA, SB and health-related outcomes, as well as to assess the effectiveness of PA and SB interventions (Gorman et al., 2014; Dogra et al., 2017). In large scale studies, self-reported measures have been used often, but questionnaires tend to overestimate PA and underestimate SB; particularly in older adults due to recall issues and social desirability bias (Ryan et al. 2018). Objectively measuring PA and SB using accelerometry gives a more detailed and accurate picture of individuals' movement behavior (Gorman et al., 2014; Karas et al., 2019). The number of studies implementing accelerometers in older adults has greatly increased over the last 10 years due to their availability and ease of use (Shiroma, Shrack & Harris, 2018). Accelerometers are being more routinely used in large scale population studies such as the UK Biobank (Doherty et al., 2017). However, despite the large amount of data provided and the ability to continuously monitor behaviors during free-living conditions and categorize activities into different intensities, numerous decisions need to be taken during data collection (e.g. minimising the loss of data) and data analysis (e.g. choice of filter) processes.

A recent paper by Dall et al. (2018) highlights a robust framework for collection of accelerometry data in large-scale studies addressing wear-time compliance, minimising the loss of data and ensuring the quality of collected data. Once the accelerometry data has been collected, data needs to be processed carefully before analysis. A recent review has highlighted the most common settings for which decisions need to be made when processing ActiGraph accelerometer data and given recommended settings across different age groups; including older adults (Migueles et al., 2017). These recommendations included choice of wear-time algorithm, choice of filter, epoch length, minimum number of wear-time minutes per day and acceptable number of days. Gorman and colleagues (2014) have also conducted a systematic review which highlighted the impact of different thresholds on SB and moderate-vigorous PA (MVPA) levels. However, some of these settings may be based on popular choice rather than validated research, such as recommending using 60-second epoch lengths in older adults (Migueles et al., 2017). As well as this, there have been no current recommendations on maximum wear-time per day. This is important to consider as many studies ask participants to remove accelerometers during periods of sleep so as not to conflate this data with SB.

Although the previous research has been useful, the consequences of using different settings on key PA and SB outcomes in older adults can be unclear. For example, older adults are more likely to walk at a reduced velocity (Bohannon 1997) and have different MVPA thresholds compared to middle-aged adults due to lower levels of cardiorespiratory fitness (Rossi Neto et al., 2019). Some assumptions using settings more specific to adult populations could have major impacts on PA and SB variables from older adults. Some examples include conflating sedentary time with non-wear-time and the incorrect exclusion of participants based on failing wear-time criteria. This is particularly important when comparing cohorts across multiple follow-up periods. Many analytical features are not one-size-fits-all and different populations require different adjustments to the analysis methods. Highlighting the consequences of using different analytical parameters on the same accelerometry dataset would therefore be useful for researchers and clinicians.

The aim of this paper is to highlight how key steps taken during data processing may affect key accelerometry outcomes (e.g. duration of sedentary time) in older adults using a selection of baseline accelerometry data collected during the xxxxx study (Giné-Garriga et al., 2017). These steps were taken in order to enhance the quality of the accelerometry data, maximize the sample size and allow accurate comparisons across the follow-up periods.

Methods

Study design and data collection

In brief, the xxxxx study is a three-armed pragmatic randomized controlled trial aiming to determine whether exercise referral schemes can be enhanced in the long-term by using self-management strategies to reduce SB, increase PA and improve health outcomes in community-dwelling older (≥65 years old) European adults; namely in Spain, Germany, Denmark and Northern Ireland (Giné-Garriga et al., 2017). Each country received ethical approval before commencing participant recruitment. Participants were instructed to wear an ActiGraph triaxial accelerometer (ActiGraph, wGT3X-BT; ActiGraph LLC, Pensacola) during waking hours only, on an elastic belt placed on their dominant hip, for seven consecutive days. The ActiGraph was initialized to sample at 30Hz. Participants recorded in an activity monitor diary when they put on the ActiGraph in the morning and when they took it off before bed as well as non-wear during the day. For this particular analysis, only the Danish (n=338) and Northern Irish (n=325) xxxxx baseline accelerometry datasets were included. However, one Danish participant failed to provide any accelerometry data due to an initialization error and four Northern Irish participants gave their consent but did not attend any baseline visits so did not provide any accelerometry data. Therefore, 337 Danish participants and 321 Northern Irish participants were included in the analysis.

Measures

Demographics: Participant characteristics included age, gender, body mass index (BMI) and overall score in the Short Physical Performance Battery (SPPB; Guralnik et al. 1994). The percentage of participants with low physical function (SPPB ≤9), based on criteria by Guralnik et al. (1995), was calculated from the results of the SPPB.

Accelerometry data processing and reasoning: Different settings were used when testing each of the analytical parameters. *Wear-time algorithms:* These help to divide wear-time and non wear-time periods. This can have a marked impact on numerous accelerometer outcomes including participant eligibility as it can affect the number of valid days included as well as the overall number of minutes which are analyzed. Two wear-time algorithms (Troiano, 2007; Choi et al., 2011) have been consistently used in the literature so were included in our analysis. The Troiano 2007 algorithm records non wear-time as ≥60 minutes of 0 CPM (vertical axis) and a spike tolerance of 2 consecutive minutes, with a spike level of ≥100 CPM (vertical axis) breaking the non wear-time cycle. The Choi 2011 algorithm was developed to use a two-window system in an attempt to provide a more robust method for calculating non wear-time; Window-1 looking for anything above 0 CPM (vertical axis) across ≥90 minutes while Window-2 looks backwards and forwards 30 minutes whenever a non-zero CPM (vertical axis) movement has been detected. Window-2 uses a non-consecutive spike tolerance of 2 minutes before determining the end of a non-wear bout. Both algorithms use 60-second epoch data as the data input. *Filtering:* It has been suggested the low frequency extension (LFE) filter should be applied to populations likely to be completing most of their movements at low intensities, such as older adults (Migueles et al. 2017). The function of the LFE filter is to increase sensitivity at collecting accelerations at the lower end of the bandpass frequency range as some of these movements may not be collected in populations with lower physical function such as older adults who are frail using the normal filter range (i.e. 0.25-2.5 Hz). Nevertheless, the LFE filter may impact key accelerometry outcomes such as SB. Therefore, analysis was performed using the LFE filter versus the normal filter. *Epoch length:* This essentially is the time window in which data is summarized before data scoring. Older studies using accelerometers used higher epoch lengths such as 60 seconds due to memory issues with the accelerometers although it is now possible to use lower epoch lengths as the technology has advanced. Therefore, we used 10 seconds and 60 seconds time windows. These two steps (*filtering* and *epoch length*) were completed firstly in those with high physical function (SPPB >9) before being completed in those with low physical function (SPPB ≤9). We split the sample for this comparison as lower functioning participants are likely to complete more low-intensity movements. *Minimum wear-time per day:* Selecting this criteria is important as the chosen threshold suggests the minimum number of daily minutes by which authors feel their participants have worn the accelerometer for a sufficient period of time to represent a valid day. The thresholds included ≥360 minutes, ≥480 minutes, ≥600 minutes and ≥720 minutes. *Maximum wear-time per day:* Some participants may wear the ActiGraph during night-time sleeping which conflates with SB and makes it difficult to determine waking hours SB time. The number of days in which participants exceeded specified maximum daily wear-time was assessed using ≥960 minutes, ≥1020 minutes, ≥1080 minutes and ≥1140 minutes. *Applying log diaries:* The final comparison was with and without log diaries being applied to datasets exceeding a specified daily wear-time threshold in an effort to remove periods of sleep in applicable participants. For the log diary comparison, the only variable not analyzed was wear-time percentage as the log diary was applied after the datasets underwent wear-time validation; meaning the participants' wear-time percentages would not be influenced by applying the log diary.

The ActiGraph variables of interest included: prevalence of participants with ≥4 valid days; average vertical axis counts per minute (CPM); average vector magnitude CPM; daily SB time; daily light PA time; daily MVPA time; daily step counts; and wear-time percentage (%). Troiano 2008 cut points were used as the scoring thresholds for the different SB and PA intensities in every setting comparison (Troiano et al., 2008). SB was classified <100 CPM, light PA 100-2019 CPM and MVPA ≥2020 CPM. To be included in each comparison, the participant was needed to have at least four valid days with one valid weekend day. These criteria have been utilized in other studies in older adults (Gorman et al., 2014). In particular, the minimum number of days requirement for older adults has been explored in past studies (Hart et al., 2011) and more recently (Ricardo et al., 2019; Sasaki et al., 2018).

Statistical analysis

Descriptive statistics included means and standard deviations (SD) while frequencies and percentages (%) were calculated when appropriate. Differences in settings across the various analytical parameters were assessed using paired sample t-tests and repeated measures ANOVAs, with Bonferroni correction to account for multiple testing used during each analysis. This was completed for the whole sample and also for each sample separately (see Supplementary Material). Only within-site differences in the analytical parameters were calculated as the objective was not to compare differences between sites. A chi-square test was used to look for differences in the frequencies of days meeting specific maximum daily wear-time thresholds. Statistical analyses were performed using SPSS Statistics version 22 (IBM, Somers, NY) and statistical significance was set at $p<0.05$. To understand the impact of the different settings on the ActiGraph variables, effect sizes (d) were calculated for each setting (Cohen, 1988). Effect sizes were classified as negligible / trivial (<0.2), small (0.20-0.49), medium (0.50-0.79) and large (≥0.80) (Cohen, 1988).

Results

Demographic details

The mean age of the 658 participants was 75.1 (SD=6.2) years and 55.9% were female (Table 1). Four participants did not provide BMI and SPPB score data. Most participants were classified as 'overweight' (mean=28.2 (SD=5.1) kg/m^2) and many were highly functioning; 85.0% had a SPPB score >9. All the results for each site are provided in the Supplementary Material (Tables S1-S7).

Comparisons of the different analytical parameters

Wear-time algorithms: In terms of the prevalence of participants with ≥4 valid days, 636 participants (96.7%) were included using the Choi 2011 algorithm whereas 574 participants (87.2%) were included using the Troiano 2007 algorithm; a difference of 62 participants. When comparing the same participants, **Table 2** shows that vertical axis CPM (-17.9 CPM), vector magnitude CPM (-40.4 CPM), daily light PA time (-3.9 minutes) and daily step counts (-59 steps) were significantly lower when using the Choi 2011 versus Troiano 2007 algorithm ($p<0.001$). Daily SB time (+81.3 minutes) and % wear-time (+7.6%) were significantly higher using the Choi 2011 versus Troiano 2007 algorithm ($p<0.001$). Daily MVPA time was not significantly different using both algorithms ($p=0.094$). These patterns were similar across both sites (see Supplementary Material).

Filtering and epoch length: When the LFE filter was used for both 10-second and 60-second epoch lengths, 543/556 participants (97.7%) with high physical function were included with ≥4 valid days. When using the normal filter for both 10-second and 60-second epoch lengths, three extra participants were excluded due to insufficient wear-time (540/556; 97.1%). Using the LFE filter for both epoch lengths resulted in significantly higher vertical axis CPM (between +33.1 and +33.4 CPM), vector magnitude CPM (between +69.6 and +70.1 CPM), daily step counts (between +6524 and +6581 steps) and percentage wear-time (+1.1%) compared to using the normal filter ($p<0.001$), whereas epoch length appeared to have no significant impact (**Table 3**). Daily SB, daily light PA and daily MVPA times were all significantly different across each of the four combinations ($p<0.001$). Using the LFE filter for both epoch lengths appeared to reduce daily SB time (between -23.6 and -27.1 minutes) while using the 10-second epoch length increased daily SB time (between +75.7 and +79.2 minutes) compared to 60-second epoch length. Daily MVPA time also increased with the LFE filter on (between +2.1 to +3.1 minutes) compared with the normal filter and the 10-second epoch length (between +8.5 and +9.6 minutes) compared with 60-second epoch length. Daily light PA time increased when using the LFE filter compared to the normal filter (between +33.5 and +38.0 minutes) but decreased when using the 10-second epoch length compared to the 60-second epoch length (between -84.2 and -88.6 minutes).

In terms of the prevalence of low function participants with ≥4 valid days, 95/98 participants (96.9%) were included when using the LFE filter whereas one extra participant was removed when using the normal filter (94/98; 95.9%) for both 10-second and 60-second epoch lengths. In general, the patterns of significant differences seen in the higher functioning participants were replicated in those with lower physical function (**Table 4**). However, daily SB time in the lower functioning participants did not significantly change when using the LFE filter compared with using the normal filter.

Minimum wear-time per day: As the minimum wear-time per day thresholds become more conservative (i.e. increasing times), more participants were removed. Prevalence of participants with ≥4 valid days across the thresholds was 648 (98.5%) for ≥360 minutes, 645 (98.0%) for ≥480 minutes, 636 (96.7%) for ≥600 minutes and 598 (90.9%) for ≥720 minutes. **Table 5** highlights the effects of each minimum wear-time per day threshold on the scoring variables. Using ≥720 minutes as the threshold reduced percentage wear-time by 1.4%, 2.8% and 5.0% compared to ≥600 minutes, ≥480 minutes and ≥360 minutes thresholds, respectively (p<0.001). Daily SB and light PA times along with daily step counts all increased significantly between ≥360 minutes versus ≥480 minutes versus ≥600 minutes versus ≥720 minutes thresholds respectively (p<0.001). Vertical axis CPM was significantly decreased between ≥360 minutes versus ≥600 minutes (p=0.029) and between ≥360 minutes versus ≥720 minutes (p=0.008). There were no differences in vector magnitude across any of the thresholds. The Danish and Northern Irish samples both followed similar patterns in the differences between settings (see Supplementary Material).

Maximum wear-time per day: Table 6 shows the spread of participants above certain maximum daily wear-time thresholds; from one day to >5 days. Using the most liberal threshold (i.e. ≥960 minutes/day) resulted in 273 participants (41.5%) having at least one valid day above the threshold. Moving from ≥1020 minutes/day, ≥1080 minutes/day and ≥1140 minutes/day thresholds resulted in 121 (18.4%), 77 (11.7%) and 62 (9.4%) participants having at least one valid day above the threshold respectively. This pattern was similar across sites (see Supplementary Material) although the Northern Irish sample had much fewer participants reaching the highest threshold ≥1140 minutes/day (n=58; 17.2% versus n=4; 1.2%).

Applying log diaries: Using the most conservative maximum threshold (≥1140 minutes), the prevalence of participants using the Choi 2011 algorithm, the normal filter, 10-second epochs, ≥600 daily wear-time minutes, ≥4 valid days with ≥1 weekend day was 636 (96.7%). **Table 7** shows that applying the log diaries for relevant participants resulted in significantly higher vertical axis CPM (+2.5 CPM) and vector magnitude CPM (+6.7 CPM) whereas daily SB (-27.4 minutes) and daily light PA (-1 minute) times decreased significantly after applying the log diary (p<0.001). Daily MVPA time and daily step counts did not significantly change. Only daily SB time significantly changed (p=0.049) in the Northern Irish sample, whereas the Danish sample followed a similar pattern to the total sample (see Supplementary Material).

Effect sizes: Table 8 shows the effects of using different settings on the analytical parameters for processing accelerometry data in older adults. Choosing different wear-time algorithms resulted in medium effects on SB and percentage wear-time and a small effect on vector magnitude CPM. Different filter choices resulted in large effects on step counts, small-to-medium effects on light PA, small effects on vertical axis CPM and vector magnitude CPM and negligible-to-small effects on SB and wear-time percentage. Epoch length had a large effect on light PA, small-to-medium effect on SB and small effect on MVPA. Comparing minimum wear-time per day settings with the standard ≥600 minutes used in many studies, using ≥360 minutes resulted in a small effect on SB and percentage wear-time whereas using ≥720 minutes had negligible effects on all the ActiGraph variables. Applying a maximum wear-time threshold per day had a small effect on SB but negligible effects on the other ActiGraph variables. Table S8 includes full details of all the effect size numbers.

Discussion

This study shows the marked impacts of choosing different settings of various analytical parameters including wear-time algorithms, choice of filter, epoch length, minimum wear-time per day and maximum wear-time per day on an array of SB and PA outcomes. These decisions were also shown to have an influence on wear-time percentage and ultimately the number of participants included in that particular scenario. These differences are important as they may have significant consequences on study findings (e.g. issues related to selection bias) and could also lead to studies potentially not being statistically powered if sample sizes have been calculated from variables such as vertical axis CPM.

Marked differences across all the included variables and the numbers of participants being excluded were observed when using Choi 2011 versus Troiano 2007 algorithms. There was a difference of 81.3 minutes for SB which was a medium effect; possibly because this was calculated as being non wear-time by the Troiano 2007 algorithm. There was also a significant small effect on vector magnitude CPM (40.4 CPM), significant but negligible effect on vertical axis CPM (17.9 CPM) and no impact on MVPA time (<0.1 minutes) mainly due to the very low percentage of daily MVPA performed by our older adult cohort. These results are similar to other studies in older adults (Keadle et al., 2014; Chudyk et al., 2017). Both sets of authors recommend using the Choi 2011 algorithm. This is likely to be particularly pronounced in older adult populations, as they are likely to spend more time being sedentary compared to younger populations (Matthews et al., 2008). Despite this, some studies have continued using the Troiano 2007 algorithm. With a larger focus on SB research over the past decade, it is imperative that authors select the most appropriate wear-time algorithm whether it is to measure SB as part of an observational study or trying to determine the effectiveness of a SB reduction intervention.

Regarding the choice of filter, the current study supports other studies regarding the impact on different variables. There were large effects on SB time, small-to-medium effects on light PA time and small effects on vertical axis CPM and vector magnitude CPM when using different filter settings. Wanner and colleagues (2013) assessed the impact of using the LFE filter compared to using the normal filter in a mixed group of middle-aged and older adults. Daily SB time decreased by 25.7 minutes while vertical axis CPM (+37.8 CPM), daily light PA time (+31.5 minutes), daily MVPA time (+3.1 minutes) and daily step counts (+7424 steps) all increased when applying the LFE filter versus using the normal filter. Other studies by Wallén et al. (2014) in patients with Parkinson's disease and Barreira et al. (2013) exclusively in older adults also found this same pattern; particularly highlighting the noticeably higher daily step counts. However, some studies have recommended using the LFE filter in older adults (Migueles et al., 2017) while others have suggested only using the normal filter (Wallén et al., 2014). When we compared filter choices in our sample of older adults with lower physical function, only SB time was not significantly affected whereas light PA and percentage wear-time were significantly different. The LFE filter may have started re-classifying non wear-time as SB while some previously classified SB went up to the light PA category. Researchers need a degree of caution when using the LFE filter for processing accelerometry data in older adults. From the literature, it appears the LFE filter might give an unrealistic representation of accelerometry data by wrongly including some actual non wear-time and inflating participants light PA and MVPA times; even in those with lower physical function (Barreira et al., 2013). Secondly, we considered the possible impact this decision would have across the three follow-up periods of the xxxxx study. For example, some participants previously rated as having 'low physical function' may gain back some functional capacity if they had taken part in the xxxxx program. The LFE filter might then not be appropriate as it would inflate PA and reduce SB by greater amounts in these participants. The reverse of this may also occur in longitudinal observational studies where function is likely to decline over time. Therefore, the decision to use LFE may have implications in terms of data quality in longitudinal and intervention studies with long-term follow up.

Little data exists comparing the effects of choices of different epoch lengths on SB and PA in older adults compared with children and young people (Edwardson & Gorely, 2010). Perhaps unsurprisingly, epoch length appears to have no impact on vertical axis CPM, vector magnitude CPM, daily step counts and percentage wear-time. This is because these variables are ‘absolute’ numbers; meaning they are not affected by changing between various epoch lengths as they still should emerge as the same number. On the other hand, it had a medium impact on daily SB (at least 75 minutes for high function older adults and at least 53 minutes for low function older adults), large impact on light PA (at least 84 minutes for high function older adults and at least 57 minutes for low function older adults) and small effect on MVPA (at least 8 minutes for high function older adults and at least 4 minutes for low function older adults) times when using either filter setting. These findings are important as recent research has been highlighting the potentially important role that light PA has to play in conferring health benefits; particularly in older adults as they are likely to find it more difficult to achieve the recommended MVPA guidelines (Loprinzi et al., 2015; Füzéki et al., 2017). Using higher epoch lengths, such as 60-seconds, resulted in shorter bouts of SB being mixed with short bouts of different PA intensities; ultimately resulting in reduced SB time. The vast majority of studies in older adults have collected data in 60-second epoch lengths (Gorman et al., 2014; Migueles et al., 2017). The main reasons behind this are that many of the first studies using accelerometry to measure SB and PA used low sampling frequencies (e.g. 1 Hz) and 60-second epochs lengths due to technological constraints (i.e. memory capacity). As accelerometer technology has advanced, so has device capacity to store data. This allows more detailed SB and PA data to be collected. Nonetheless, many current studies wish to compare their own data with historical datasets so continue using 60-second epochs. Using 10-second epochs is likely to provide a more realistic time-scale to summarize real-life activities of older adults (e.g. in-home transfers from room-to-room or rising from a chair) as they are presumed to be patterned and non-sporadic. However, simply using the shortest available epoch length (i.e. 1-second) may increase the likelihood of 'noise' being introduced which would very likely not be reflective of normal activity patterns in older adults. Using a more middle ground value such as 10-second epochs may provide a sustainable window length representing most typical activities in this population. Indeed, little is known on the effects of longer (>60 seconds) versus shorter (<10 seconds) bouts of SB in terms of health outcomes. Accordingly, Byrom and Rowe (2016) recommend that using the high epoch lengths may result in some SB time being wrongly classified but also suggest that using the smallest epoch lengths when measuring older adults' SB provides little additional benefit.

Interestingly, when requiring ≥4 valid days with ≥1 weekend day but increasing the minimum daily wear-time threshold from ≥360 minutes to ≥600 minutes per day did not result in many additional participants being excluded (i.e. 12) although moving to ≥720 minutes resulted in a further 38 participants being excluded. However, the impact could be seen across all of the SB and PA variables. Using lower thresholds such as ≥360 minutes and ≥480 minutes compared to ≥600 minutes and ≥720 minutes resulted in higher wear % but lower SB, light PA and MVPA times along with step counts. Using the lower daily minimum threshold limits had small effects on SB and wear-time percentage compared to using ≥600 minutes. Reviews (Gorman et al., 2014; Migueles et al., 2017) recommend and longitudinal studies (Troiano et al., 2008; Berkemeyer et al., 2016) have used valid day requirements of ≥600 minutes per day as lesser amounts of time have been shown to be significantly different; our study supports these findings although effects appear to be negligible apart from small effects on SB and MVPA times. Although the current study shows that using ≥720 minutes versus ≥600 minutes resulted in significantly higher SB time (+9.6 minutes), light PA (+2.1 minutes) and step counts (+45 steps) but lower wear-time percentage (-2.2%), we feel that the relatively high decline in participants' numbers and the negligible effect on key ActiGraph variables are important to consider.

Many studies have failed to discuss how they have dealt with participants wearing accelerometers across the whole day although Berkemeyer et al. (2016) highlighted how they truncated wear-time to 1140 minutes per day to help normalize their dataset. Having a maximum daily wear-time threshold is vitally important as there is the possibility of SB time being conflated with sleep-time if the accelerometer has not been removed. In our study, using lower thresholds such as ≥960 and ≥1020 minutes included many participants who legitimately wore the ActiGraph for these lengths of time (i.e. not during sleep). The numbers of participants meeting the ≥1080 and ≥1140 minutes limits dropped substantially. As has been recommended in a review paper (Edwardson et al., 2017), for participants meeting the selected thresholds, we used the participants' activity monitor diaries to determine whether the wear-time determined by the software was similar to the activity monitor diary to determine daily wear-time when awake. After this check was carried out across both sites, a decision was made to make 1140 minutes the threshold value as a number of the participants exceeding the 1080 minutes limit were awake for this length of time. In deciding which maximum thresholds to use, sleep time duration recommendations for older adults were also used (Hirshkowitz et al., 2015). These suggest <360 minutes sleep per day might be appropriate for some but that <300 minutes sleep per day is not recommended. Interestingly, more participants in the Danish cohort wore the accelerometer >1140 minutes compared with the Northern Irish cohort. Participants were given the same instructions to remove the ActiGraph just before they went to sleep. However, a higher number of Danish participants wore the ActiGraph throughout the night meaning they had wear-time close to 24 hours. ActiLife software allows the manual input of log diaries so this was applied to the relevant participants. This resulted in significantly higher but negligible effects on vertical axis CPM and vector magnitude CPM, significantly lower but negligible effects on light PA time and significantly lower small effect on SB time. This highlights that applying a maximum daily threshold is particularly important to those researching SB.

The key strength of the study was the array of analytical parameters being compared and contrasted against a number of commonly used objectively measured PA and SB variables. This allows researchers and clinicians to see the likely effects of different analytical choices on their own datasets. It was also focused on older adults where there has been a lack of research in some of the analytical parameters for this age group. An important point to note is that the sample was recruited for an intervention study looking to decrease SB and increase PA. Therefore, the participants needed to be somewhat mobile to be eligible to take part. This might mean the findings are not generalizable to the frailest older adults in the general population. Despite using well-referenced data scoring thresholds by Troiano and colleagues (2008), we appreciate that current cut-points might not be the best fit for older adults. Although our study provides useful information on the consequences of different analytical decisions, we are not able to give firm guidelines as this would require comparisons with direct observations. However, we felt it would be useful to provide details on the effects of using different settings for each of the analytical parameters (see **Table 8**). As large-scale studies like the UK Biobank are using other anatomical positions, a similar study exploring the different analytical variables in older adults wearing monitors in other anatomical positions may yield different findings.

Our study has shown that every decision made in the processing of older adults' accelerometry data can impact on the number of participants being included during analysis and also on SB and PA levels. Analytical decisions may therefore result in Type 1 and Type 2 errors. For example, the real impacts of a SB or PA intervention could be exaggerated or obscured. We recommend that all future older adult studies fully highlight the decisions made in the processing of their accelerometry data. As older adults can functionally vary by large amounts, future research would need to explore which analytical parameters are most suitable for high and low functioning older adults. There is also a need for carefully controlled, laboratory-based validation studies in an attempt to accurately determine the most appropriate settings to be used in older adults such as epoch length and choice of filter.

Acknowledgements

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Table 1. Descriptive characteristics of the total sample

Variable	Mean	Standard Deviation	Number with data (n=658)
Age, years	75.13	6.16	658
Gender, n	290M / 368F	-	658
BMI, kg/m^2	28.21	5.10	654
SPPB, score 0-12	10.94	1.63	654
Proportion of participants with low physical function, %	15.00	-	98

Abbreviations: BMI = body mass index; F = female; kg/m^2 = kilograms per metre squared; M = male; n = number; SPPB = Short Physical Performance Battery

Table 2. Comparison of PA and SB variables for different wear-time algorithms for the total sample

Combination - **Normal filter** - **60-sec epoch** - **≥600 mins** - **≥4 days** - **≥1 weekend day**	**Vertical Axis CPM**	**Vector Magnitude CPM**	**Daily SB time (mins)**	**Daily Light PA time (mins)**	**Daily MVPA time (mins)**	**Daily step counts**	**Wear %**
			Total (n=574) (mean (SD))				
Choi 2011	207.82 (112.70)*	444.25 (174.01)*	629.15 (138.99)*	250.97 (71.65)*	17.14 (19.34)	5361 (2749)*	54.95 (12.44)*
Troiano 2007	225.74 (114.30)	484.65 (172.78)	547.81 (86.91)	254.90 (70.78)	17.23 (19.38)	5420 (2745)	47.33 (10.64)

Abbreviations: CPM = counts per minute; mins = minutes; MVPA = moderate-vigorous physical activity; n = number; PA = physical activity; sec = seconds; SB = sedentary behavior; SD= standard deviation
*p<0.001

Table 3. Comparison of PA and SB variables for different filter choices and epoch lengths in the total sample with high physical function (Guralnik >9 SPPB)

Combination - Choi 2011 - ≥600 mins - ≥4 days - ≥1 weekend day	Vertical Axis CPM	Vector Magnitude CPM	Daily SB time (mins)	Daily Light PA time (mins)	Daily MVPA time (mins)	Daily step counts	Wear %
			Total (n=540) (mean (SD))				
10-second; LFE on	244.64 (119.88) [a,c]	517.76 (190.13) [a,c]	673.50 (131.92) [a,b,c]	198.92 (54.72) [a,b,c]	29.41 (23.05) [a,b,c]	12024 (3809) [a,c]	55.00 (12.97) [a,c]
10-second; LFE off	211.29 (112.68) [d]	447.64 (172.88) [d]	697.08 (119.92) [d,e]	165.39 (48.70) [d,e]	26.28 (21.92) [d,e]	5443 (2736) [d]	53.88 (12.29) [d]
60-second; LFE on	244.38 (120.02) [f]	517.24 (190.39) [f]	594.30 (139.98) [f]	287.54 (76.67) [f]	19.85 (20.32) [f]	11967 (3866) [f]	54.99 (12.96) [f]
60-second; LFE off	211.29 (112.68)	447.64 (172.88)	621.43 (128.65)	249.54 (72.59)	17.78 (19.42)	5443 (2736)	53.88 (12.29)

Abbreviations: CPM = counts per minute; LFE = low-frequency extension; mins = minutes; MVPA = moderate-vigorous physical activity; n = number; PA = physical activity; SB = sedentary behavior; SD = standard deviation

[a] 10-second; LFE on versus 10-second; LFE off ($p<0.001$)
[b] 10-second; LFE on versus 60-second; LFE on ($p<0.001$)
[c] 10-second; LFE on versus 60-second; LFE off ($p<0.001$)
[d] 10-second; LFE off versus 60-second; LFE on ($p<0.001$)
[e] 10-second; LFE off versus 60-second; LFE off ($p<0.001$)
[f] 60-second; LFE on versus 60-second; LFE off ($p<0.001$)

Table 4. Comparison of PA and SB variables for different filter choices and epoch lengths in the whole sample with low physical function (Guralnik ≤9 SPPB)

Combination - Choi 2011 - ≥600 mins - ≥4 days - ≥1 weekend day	Vertical Axis CPM	Vector Magnitude CPM	Daily SB time (mins)	Daily Light PA time (mins)	Daily MVPA time (mins)	Daily step counts	Wear %
Total (n=94) (mean (SD))							
10-second; LFE on	144.82 (87.13) [a,c]	355.26 (168.20) [a,c]	748.26 (179.30) [b,c]	162.74 (57.99) [a,b,c]	12.07 (13.92) [a,b,c]	8628 (3262) [a,c]	58.71 (14.91) [a,c]
10-second; LFE off	119.14 (78.01) [d]	303.76 (148.62) [d]	748.40 (147.06) [d,e]	129.02 (51.56) [d,e]	10.38 (13.01) [d,e]	3062 (2089) [d]	55.12 (13.52) [d]
60-second; LFE on	144.46 (87.19) [f]	354.54 (168.33) [f]	688.68 (189.63)	227.20 (82.04) [f]	7.19 (12.28) [f]	8564 (3310) [f]	58.71 (14.91) [f]
60-second; LFE off	119.14 (78.01)	303.76 (148.62)	694.79 (157.44)	186.84 (78.28)	6.18 (11.62)	3062 (2089)	55.12 (13.52)

Abbreviations: CPM = counts per minute; LFE = low-frequency extension; mins = minutes; MVPA = moderate-vigorous physical activity; n = number; PA = physical activity; SB = sedentary behavior; SD = standard deviation

[a] 10-second; LFE on versus 10-second; LFE off ($p<0.001$)
[b] 10-second; LFE on versus 60-second; LFE on ($p<0.001$)
[c] 10-second; LFE on versus 60-second; LFE off ($p<0.001$)
[d] 10-second; LFE off versus 60-second; LFE on ($p<0.001$)
[e] 10-second; LFE off versus 60-second; LFE off ($p<0.001$)
[f] 60-second; LFE on versus 60-second; LFE off ($p<0.001$)

Table 5. Comparison of PA and SB variables for different minimum wear-time per day thresholds for the whole sample

Combination - Choi 2011 - Normal filter - 10-sec epoch - ≥4 days - ≥1 weekend day	Vertical Axis CPM	Vector Magnitude CPM	Daily SB time (mins)	Daily Light PA time (mins)	Daily MVPA time (mins)	Daily step counts	Wear %
Total (n=598) (mean (SD))							
≥360 minutes	201.42 (114.78) [b,c]	431.94 (178.96)	681.53 (118.61) [a,b,c]	156.18 (49.33) [a,b,c]	23.88 (21.21) [a,b,c]	5025 (2710) [a,b,c]	57.79 (12.31) [a,b,c]
≥480 minutes	201.03 (114.54)	431.58 (178.65)	698.86 (122.24) [d,e]	160.16 (49.94) [d,e]	24.33 (21.71) [d,e]	5139 (2774) [d,e]	56.38 (12.16) [d,e]
≥600 minutes	200.70 (114.21)	431.02 (178.22)	710.36 (126.31) [f]	162.56 (50.40) [f]	24.58 (21.88)	5200 (2792) [f]	54.99 (12.14) [f]
≥720 minutes	200.29 (113.61)	430.67 (178.41)	719.99 (129.07)	164.65 (50.76)	24.72 (21.91)	5245 (2801)	52.75 (12.98)

Abbreviations: CPM = counts per minute; mins = minutes; MVPA = moderate-vigorous physical activity; n = number; PA = physical activity; SB = sedentary behavior; SD = standard deviation; sec = seconds

[a] ≥360 minutes versus ≥480 minutes ($p<0.05$)
[b] ≥360 minutes versus ≥600 minutes ($p<0.05$)
[c] ≥360 minutes versus ≥720 minutes ($p<0.05$)
[d] ≥480 minutes versus ≥600 minutes ($p<0.05$)
[e] ≥480 minutes versus ≥720 minutes ($p<0.05$)
[f] ≥600 minutes versus ≥720 minutes ($p<0.05$)

Table 6. The numbers of participants exceeding the specified maximum daily wear-time thresholds in the total sample

Combination - **Choi 2011** - **Normal filter** - **10-sec epochs** - **No minimum day limits**	**0 days**	**1 day**	**2 days**	**3 days**	**4 days**	**5+ days**
		Total (n=658)				
≥960 minutes, n (%)	385 (58.5)	98 (14.9)	45 (6.8)	36 (5.5)	27 (4.1)	67 (10.2)
≥1020 minutes, n (%)	537 (81.6)	47 (7.1)	18 (2.7)	6 (0.9)	2 (0.3)	48 (7.3)
≥1080 minutes, n (%)	581 (88.3)	27 (4.1)	4 (0.6)	2 (0.3)	4 (0.6)	40 (6.1)
≥1140 minutes, n (%)	596 (90.6)	15 (2.3)	5 (0.8)	3 (0.5)	2 (0.3)	37 (5.6)

Abbreviations: n = number; sec = seconds

Table 7. Comparison of PA and SB variables when applying and not applying log diaries eliminating maximum wear-time ≥1140 minutes for the whole sample

Combination - **Choi 2011** - **Normal filter** - **≥10-sec epoch** - **≥600 mins** - **4 days** - **≥1 weekend day**	**Vertical Axis CPM**	**Vector Magnitude CPM**	**Daily SB time (mins)**	**Daily Light PA time (mins)**	**Daily MVPA time (mins)**	**Daily step counts**
Total (n=636) (mean (SD))						
Not applying log diaries for relevant participants	197.56 (112.88)*	426.30 (176.71)*	704.46 (125.40)*	160.09 (50.83)*	23.88 (21.56)	5086 (2778)
Applying log diaries for relevant participants	200.06 (112.08)	433.01 (174.64)	677.10 (70.81)	159.11 (51.59)	23.85 (21.60)	5079 (2791)

Abbreviations: CPM = counts per minute; mins = minutes; MVPA = moderate-vigorous physical activity; n = number; PA = physical activity; SB = sedentary behavior; SD = standard deviation; sec = seconds
*p<0.001

Table 8. Effects of using different settings on the analytical parameters for processing accelerometry data in older adults

Analytical parameter	Magnitude of effects
Wear-time validation	*Troiano 2007 versus Choi 2011* ↑↑ SB, % Wear ↑ Vector Magnitude CPM ↔ Vertical Axis CPM, Light PA, MVPA, Step Counts
Filter choice (applies to both 10-seconds & 60-seconds epoch length unless otherwise stated)	*LFE filter versus normal filter (high physical function)* ↑↑↑ Step Counts ↑↑ Light PA ↑ Vertical Axis CPM, Vector Magnitude CPM, SB (60-seconds epoch only) ↔ SB (10-seconds epoch only), MVPA, Wear % *LFE filter versus normal filter (low physical function)* ↑↑↑ Step Counts ↑↑ Light PA (10-seconds epoch only) ↑ Vertical Axis CPM, Vector Magnitude CPM, Light PA (60-seconds epoch only), Wear % ↔ SB, MVPA
Epoch length (applies to both LFE filter and normal filter unless otherwise stated)	*10-second versus 60-second (high physical function)* ↑↑↑ Light PA ↑↑ SB ↑ MVPA ↔ Vertical Axis CPM, Vector Magnitude CPM, Step Counts, % Wear *10-second versus 60-second (low physical function)* ↑↑↑ Light PA ↑ SB, MVPA ↔ Vertical Axis CPM, Vector Magnitude CPM, Step Counts, % Wear
Minimum wear-time per day	*600 minutes versus 360 minutes* ↑ SB, Wear % ↔ Vertical Axis CPM, Vector Magnitude CPM, Light PA, MVPA, Step Counts *600 minutes versus 720 minutes*

	↔ Vertical Axis CPM, Vector Magnitude CPM, SB, Light PA, MVPA, Step Counts, % Wear
Maximum daily threshold	*No maximum threshold versus applying ≥1140 minutes threshold* ↑ SB ↔ Vertical Axis CPM, Vector Magnitude CPM, Light PA, MVPA, Step Counts

Abbreviations: ↔ = trivial / negligible effect; ↑ = small effect; ↑↑ = medium effect; ↑↑↑ = large effect; CPM = Counts per minute; LFE = Low-frequency extension; MVPA = Moderate-vigorous physical activity; PA = Physical activity; SB = Sedentary behavior